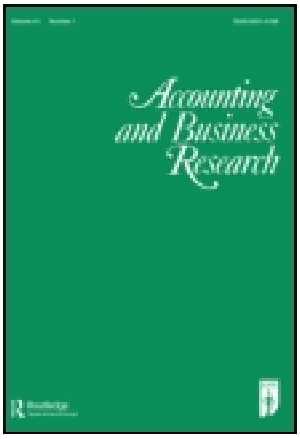

Accounting and Business Research
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/rabr20

Earnings quality, bankruptcy risk and future cash flows

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Published online: 04 Jan 2011.

To cite this article: Ali Al-Attar, Simon Hussain & Ling Yan Zuo (2008) Earnings quality, bankruptcy risk and future cash flows, Accounting and Business Research, 38:1, 5-20, DOI: 10.1080/00014788.2008.9663317

To link to this article: http://dx.doi.org/10.1080/00014788.2008.9663317

Earnings quality, bankruptcy risk and future cash flows

Ali Al-Attar, Simon Hussain & Ling Yan Zuo*

Abstract—Prior research suggests that the quality of accruals may be compromised where the magnitude of accruals is abnormally high, due to the presence of errors in the accruals-estimation process (Dechow and Dichev, 2002; Richardson, 2003). A consequence of this is that abnormal accruals may not map into realised future cash flows to the extent that would normally be expected of accruals data. Indeed, the association may be insignificant if abnormal accruals consist primarily of estimation noise. Our study investigates whether abnormal accruals for UK firms provide incremental insight into future cash flows. In particular, our paper may be viewed as a development of Subramanyam (1996). We find a significant positive association between abnormal accruals and one-year-ahead operating cash flows. This provides a rationale for the pricing of abnormal accruals by the market (Subramanyam, 1996; Xie, 2001) and suggests that abnormal accruals are not merely the products of noise in the accruals-estimation process. However, our results are conditional upon the probability of one-year-ahead bankruptcy risk (Charitou et al., 2004). We also find that abnormal accruals possess small but significant explanatory power for future cash flows even when controlling for the disaggregation of accruals into individual items (Barth et al., 2001).

Key words: earnings quality; bankruptcy risk; operating cash flows; future cash flows; abnormal accruals; working capital accruals

1. Introduction

Evidence from both US and UK studies supports the hypothesis that accruals contain significant explanatory power for future cash flows, over and above that contained in current cash flow data (e.g. Barth et al., 2001; Al-Attar and Hussain, 2004). The use of accrual accounting to construct *accounting earnings* is intended to give a superior insight into future cash flows than could be gleaned from current cash flow data alone (FASB, 1978, para. 44; Beaver, 1989: 6–7). Accruals mitigate timing and mismatching problems inherent in measuring cash flows over short intervals (Dechow, 1994; Dechow et al. 1998).

However, managers may use accruals to manage earnings opportunistically and thereby adversely affect the quality of reported earnings with regard to conveying information on future cash flows. Even in the absence of deliberate manipulation by managers, large accruals may be associated with a reduced quality of reported earnings due to increased measurement errors in managers' accruals estimates: this point has been noted in studies by Dechow and Dichev (2002), Richardson (2003), Li et al. (2003) and Bharath et al. (2004). Indeed, Dechow and Dichev (2002: 36–37, 47) hypothesise that if abnormally large accruals are associated with high levels of estimation error then such accruals will not map into realised future cash flows to the extent that would normally be expected of accruals data. However, we also know that the market considers abnormal accruals to be value-relevant (Subramanyam, 1996; Xie, 2001). Our aim is to examine whether abnormal accruals for UK firms possess significant explanatory power for future cash flows, or if they are merely noisy data with little information content. We focus on abnormal working capital accruals following Peasnell et al. (2000, 2005) and employ a test methodology used previously by Subramanyam (1996). Subramanyam decomposes accounting earnings into cash flows, normal and abnormal accruals, and examines the explanatory power of these components with regard to future cash flows using OLS regression analysis.

Evidence to support the utility of abnormal accruals comes from Xie (2001) who finds that abnormal (discretionary) accruals have value-relevance in the market place. This finding suggests either that the market is inefficient and is valuing the discretionary component of earnings, or that

*Ali Al-Attar is at Hashemite University, Jordan. Simon Hussain and Ling Yan Zuo are at the University of Newcastle upon Tyne, UK. They gratefully acknowledge former and current editors (Prof. Ken Peasnell and Prof. Pauline Weetman) together with two anonymous referees. All have provided detailed and thoughtful suggestions throughout the review process, especially regarding the aims of the study and the metrics employed. Their time and effort is very much appreciated. They also wish to thank Prof. Krishna Paudyal (Durham) and Dr David Oldroyd (Newcastle) for their comments on the doctoral research that formed the original basis for this investigation.

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This paper was accepted for publication in August 2007.

abnormal accruals contain information regarding future cash flows that is not contained in reported cash flows or accruals items. Of course it must be remembered that abnormal accruals reflect a broader information set than reported accruals because the calculation of abnormal accruals usually requires time-series or cross-sectional analysis. Further evidence for the utility of abnormal accruals is found by Subramanyam (1996) who reports that abnormal accruals display a strong positive association with one-year-ahead operating cash flows, and are similarly correlated with stock returns. Subramanyam (1996: 272) notes that a possible explanation for these findings is that managers may sometimes use abnormal accruals to signal private information regarding future performance, consistent with Healy and Palepu (1993).

Methodologically, our paper develops Subramanyam's study in two ways. First, we examine the information content of abnormal accruals within a framework that allows for variations in bankruptcy risk within our sample. Several US studies have suggested that bankruptcy risk may be a contextual factor influencing the information content of current accounting data vis-à-vis future cash flows, as proxied by stock returns. Frankel (1992) finds that for those companies that have bond ratings below BBB, the relation between stock returns and cash flows is weakened. Hanna (1995) reports that the information content of cash flows is conditional on a firm's financial position assessed using the Ohlson (1980) bankruptcy probability model. Examining the relation between cash flows and cumulative abnormal returns, Hanna finds the association is insignificant for the extreme bankruptcy quintiles. Since Subramanyam models future cash flows as a function of current cash flows and accruals, it follows that the slope coefficients for these variables may interact with the level of bankruptcy risk. In particular, the slope coefficients may be reduced at higher risk levels if these prior findings hold for our data.

Our second development of Subramanyam's study is to examine the information content of abnormal accruals within a framework that controls for individual accruals items. Barth et al. (2001) and Al-Attar and Hussain (2004) report that the disaggregation of total accruals into individual items leads to significant improvements in the explanatory power of current accounting data for one-year-ahead operating cash flows. It is possible that the information content released through the full disaggregation of accruals may exhaust the information content of abnormal accruals – this is an issue not examined by Subramanyam.

2. Sample and methodology

2.1. Sample

The data for this study are extracted from *Datastream* for London Stock Exchange listed UK firms for each year from 1994 to 2004, inclusive.[1] Firms in the finance sector are excluded because of differences in the components of their financial statements relative to the non-finance sector, and for consistency with prior studies.[2] We include dead firms across the test period using the special search function within *Datastream*, thus avoiding any survivorship bias within our sample. Data for dead firms represents 36% of the observations within our sample. Firms are members of the following industry sectors: mineral extraction; building and construction; chemicals; electricals; engineering; paper and packaging; food production; household goods; healthcare; pharmaceuticals; hotels and leisure; media; retailers; pubs, breweries and restaurants; business support services; IT and computing; transport; utilities. The selection criteria are that accounting data be available to estimate abnormal accruals (see below) and that each sector-year category contains no less than 10 observations. This gives a sample of 4,024 firm-year observations.

The estimation of abnormal accruals follows the approach used in studies by Peasnell, Pope and Young (2000, 2005), denoted PPY hereinafter. They use a cross-sectional version of the modified Jones model and focus on working capital accruals rather than total operating accruals. Their rationale for this focus is that systematic earnings management via the depreciation accrual is likely to have limited potential (see Beneish, 1999). We continue with this line of reasoning but generate two measures of abnormal accruals. Our first measure of abnormal accruals follows PPY directly. We estimate regression equation 1 for each combination of sector (s) and year (t) where there are 10 observations or more.[3] Following Jones (1991) and many similar studies, we deflate all variables by lagged total assets:

$$WC_{j,s,t} = \alpha_{0,s,t} + \alpha_{1,s,t}.(\Delta REV_{j,s,t} - \Delta REC_{j,s,t}) + \tau_{j,s,t} \quad (1)$$

where $WC_{j,s,t}$ = working capital accruals for firm j (in sector s and year t) = the change in non-cash current assets minus the change in current liabilities; $\Delta REV_{j,s,t}$ = the change in revenues from year t-1 to t; $\Delta REC_{j,s,t}$ = the change in receivables from year t-1 to t; $\alpha_{0,s,t}$ and $\alpha_{1,s,t}$ are the model parame-

[1] During the test period for this study, UK firms reported cash flow data under FRS 1, *Cash Flow Statements* (ASB 1991, revised 1996).

[2] Constituents: FTSE-100 (15%); FTSE Mid-250 (38%); FTSE Small Cap. (47%).

[3] Peasnell et al. (2005, footnote 9) state that they estimate two versions of this model, one following our equation 1 and another with the intercept suppressed and replaced by the reciprocal of total assets. Both generate substantially the same results.

ters estimated for sector s and year t; $\tau_{j,s,t}$ = the residual error (our abnormal accruals estimate AA1).

In this regression, the residual error (τ) is the difference between the realised value for $WC_{j,s,t}$ and the estimated or normal value. Thus, the residual error gives our first estimate of abnormal accruals, which we denote AA1. It should be noted that in some papers the ΔREC term is omitted from the regression estimation, but included when calculating the abnormal accruals value. However, Peasnell et al. note that results are materially unchanged using either approach (Peasnell et al., 2000, endnote 9).

Our second estimate of abnormal accruals takes account of the results reported by Jeter and Shivakumar (1999). They suggest that cash flows from operations may be related to accruals even in the absence of earnings management and note that studies by Rees et al. (1996), Hansen and Sarin (1996) and Shivakumar (1997) have included cash flows within the Jones model. Following their approach, we adjust the PPY estimation model thus:

$$WC_{j,s,t} = \theta_{0,s,t} + \theta_{1,s,t}.(\Delta REV_{j,s,t} - \Delta REC_{j,s,t}) + \theta_{2,s,t}.OCF_{j,s,t} + \delta_{j,s,t} \quad (2)$$

where $OCF_{j,s,t}$ = cash flows from operations for firm j (in sector s and year t); $\theta_{0,s,t}$, $\theta_{1,s,t}$ and $\theta_{2,s,t}$ are the model parameters estimated for sector s and year t; $\delta_{j,s,t}$ = the residual error (our abnormal accruals estimate AA2).

Again, we use the residual error (δ) to represent abnormal accruals. This gives us a cash flow-adjusted version of the PPY model, and a second measure of abnormal accruals, denoted AA2.[4]

The use of a cross-sectional regression estimation method implies that each sector-year has a mean abnormal accrual value of zero. Essentially, by choosing this approach we are comparing each actual observation to the expected value derived from a regression model for the sector-year category to which the observation belongs. These cross-sectional models assume implicitly that the model parameters are the same across all firms in the sector-year category. In theory, this could pose problems in cases where all firms within a given sector-year manipulate earnings in a similar and systematic manner. However, the main alternative to this cross-sectional sector-year approach is to estimate firm-specific models using time series data, which introduces different problems. For example, such models require the assumption of temporal stability in the model parameters and impose restrictive survivorship requirements on a sample's constituent firms. In addition, they need to be estimated across time periods that are free of earnings manipulation, which are not easily identifiable. The sector-year approach makes no assumptions on this issue (see Jeter and Shivakumar, 1999: 301) and imposes less restrictive data requirements.

Our bankruptcy risk measure is calculated using the one-year-ahead bankruptcy probability model estimated by Charitou et al. (2004) for UK public non-financial firms. Their model takes the form:

$$\ln\left(\frac{P}{1-P}\right)_{j,t} = w_1.TLTA_{j,t} + w_2.EBITTL_{j,t} + w_3.CFOTL_{j,t} + \kappa \quad (3)$$

where P = probability of bankruptcy one year ahead; TLTA = total liabilities ÷ total assets; EBITTL = earnings before interest and tax ÷ total liabilities; CFOTL = cash flows from operations ÷ total liabilities; w = ratio weightings (w_1 = 12.38, w_2 = –20.96, w_3 = –3.01); κ = constant (–7.17).

These data are employed within a multivariate regression framework. This is discussed below.

2.2. *Test methodology*

Most prior UK studies on the usefulness of accounting data for explaining future cash flows have been price-based, examining price levels, returns or cumulative abnormal returns (e.g. Board and Day, 1989; Ali and Pope, 1995; Clubb, 1995; McLeay et al., 1997; Charitou and Clubb, 1999; Garrod et al., 2003). In such studies it is necessary to assume that prices reflect information about future cash flows in an efficient manner. We utilise an alternative approach by examining the ability of accounting data to explain *actual* future cash flow data.

We develop the Subramanyam model to include bankruptcy risk as an interactive variable, in conjunction with Subramanyam's three main explanatory variables (cash flows, normal accruals and abnormal accruals). Equation 4 represents our modified version of Subramanyam's model and is estimated using OLS:

$$OCF_{i,t+1} = \lambda_0 + \lambda_1 OCF_{i,t} + \lambda_2 AA_{i,t} + \lambda_3 NA_{i,t} + \lambda_4 BR_{i,t} + \lambda_5 BR\cdot OCF_{i,t} + \lambda_6 BR\cdot AA_{i,t} + \lambda_7 BR\cdot NA_{i,t} + w_{i,t+1} \quad (4)$$

where OCF = operating cash flows; AA = abnormal accruals (for which we use two measures, AA1 and AA2 defined by equations 1 and 2); NA = normal accruals, defined as total accruals less abnormal accruals; BR = one-year-ahead bankruptcy risk, following Charitou et al. (2004); λ_0 to λ_n= model parameters, to be estimated using OLS regression; $w_{i,t+1}$ = random error term following usual OLS assumptions.

Following Subramanyam (1996) we expect the slope signs for current operating cash flows, nor-

[4] Jeter and Shivakumar allow the coefficient θ_2 to vary across different cash flow quartiles. However, this requires the addition of five cash flow variables to the model. Given the smaller numbers of observations typically available for UK sector-year categories, we include a single variable (OCF) to control for cash flows whilst preserving degrees of freedom.

$$OCF_{i,t+1} = \gamma_0 + \gamma_1 OCF_{i,t} + \gamma_2 AP_{i,t} + \gamma_3 INV_{i,t} + \gamma_4 AR_{i,t} + \gamma_5 DEP_{i,t} + \gamma_6 OTHER_{i,t} + \sum_{m=1}^{9} \gamma_{6+m}.YEAR_m + \sum_{g=1}^{17} \gamma_{15+g}.SECTOR_g + u_{i,t+1} \quad (5)$$

mal accruals and abnormal accruals in equation 4 to be positive. However, if it is the case that high bankruptcy risk is associated with a diminution of the information content of current accounting data vis-à-vis future cash flows (Frankel, 1992; Hanna, 1995) then we would expect the slopes to become smaller as bankruptcy risk reaches higher levels. As a result, we hypothesise that the slopes for the multiplicative variables will be negative. We hold no *a priori* expectation for the sign of the intercept.

The methodology described above is a modified version of Subramanyam's earnings-decomposition model, which separates earnings components into operating cash flows, normal accruals and abnormal accruals. However, papers by Barth et al. (2001) and Al-Attar and Hussain (2004) propose decomposing earnings into cash flows plus individual reported accruals items (changes in accounts payable, accounts receivable and inventories, and depreciation). These papers report that such a disaggregation of earnings provides significant additional explanatory power for future cash flows, over and above current cash flows and total accruals. We examine whether abnormal accruals retain significant explanatory power once we have controlled for Barth et al.'s form of earnings disaggregation.

We begin by estimating the full Barth et al. regression model across all firm-years, using dummy variables to control for year-effects and sector-effects in the levels of future cash flows. A dummy variable approach is used here to control for sector-year variations rather than conducting individual regressions for sector-year samples because of the number of variables in the Barth et al. model and the resulting reductions in degrees of freedom for those sector-years with little more than 10 observations. Following Barth et al. we trim our sample of the extreme percentiles for each variable. Our estimated model takes the form shown above (5), where OCF = operating cash flows; AP = change in accounts payable; INV = change in inventory; AR = change in accounts receivable; DEP = depreciation on tangible assets; OTHER = represents other accruals {reported earnings – [OCF + AR + INV – AP – DEP]}; γ_0 to γ_n = model parameters, to be estimated using OLS regression; YEAR and SECTOR are dummy variables for years and sectors; $u_{i,t+1}$ = the regression model residual.

The residual from equation 5 ($u_{i,t+1}$) represents that part of future cash flows not explained by Barth et al.'s disaggregation procedure. We examine whether abnormal accruals possess explanatory power for this element, indicating potential incremental information content and valuation relevance. For consistency with our estimation of abnormal accruals, we conduct regression equation 5 using lagged total assets as the deflator for all variables.[5] Our model includes *m* year dummies for 1994 to 2003, with 2001 being the omitted year dummy; and *g* sector dummies, with utilities being the omitted sector dummy.[6]

To examine the potential information content of disaggregating total accruals into normal and abnormal accruals – neither of which are variables in the Barth et al. model – we use the residual from the Barth et al. model (denoted RESID) as the dependent variable in regression equation 6. As before, we allow for interaction between the explanatory variables and the level of bankruptcy risk:

$$RESID_{i,t+1} = \mu_0 + \mu_1 BR_{i,t} + \mu_2 AA_{i,t} + \mu_3 NA_{i,t} + \mu_4(BR{\cdot}AA_{i,t}) + \mu_5(BR{\cdot}NA_{i,t}) + \zeta_{i,t+1} \quad (6)$$

where RESID = the residual error from equation 5; AA = abnormal accruals (for which we use two measures, AA1 and AA2 defined by equations 1 and 2); NA = normal accruals, defined as total accruals less abnormal accruals; BR = one-year-ahead bankruptcy risk, following Charitou et al. (2004); μ_0 to μ_n = model parameters, to be estimated using OLS regression; $\zeta_{i,t+1}$ = random error term following usual OLS assumptions.

It is difficult *a priori* to assess the signs of the regression coefficients for the main explanatory variables, given that there is no prior evidence on these residual cash flows. Indeed, it is possible that RESID may not display any significant association with the set of explanatory variables in equation 6 if Barth et al.'s disaggregation of total accruals exhausts the information content of abnormal accruals. However, if we assume that normal and abnormal accruals convey information about residual future cash flows in a similar manner to how they convey information about future cash flows, then they will generate slopes with the same signs as for regression equation 4.

3. The results

3.1. Descriptive statistics

We begin this section by examining the sector-year regressions for equations 1 and 2, which generate our two estimates of abnormal accruals – the PPY measure (AA1) and the cash flow-adjusted PPY measure (AA2). For the sake of brevity, Table 1 reports summary data by industry sector aver-

[5] Al-Attar and Hussain's UK study uses the number of shares as the deflator, but they state that their results are materially unaffected by using total assets as an alternative deflator.

[6] Some studies exclude utilities, but we find that our results are insensitive to this sector's inclusion/exclusion.

aged across all years, rather than for each sector-year. Values for WC, ΔREV – ΔREC and OCF are generally positive, as may be expected (Panel A). However, examination of the summary data for the regression equations displays some notable variations in the adjusted R-squared values across sectors (Panel B). This is worth noting because the regression residuals provide the estimates for abnormal accruals, and regressions with low R-squared values may tend to have a greater number of large residuals due to the inferior model-fit.

To guard against problems arising from potential outliers, the extreme 1% tails for AA1 and AA2 estimates are eliminated. It may be noted that the cash flow-adjusted PPY model often improves the degree of model-fit at the sector-year level, and this may explain why the abnormal accruals estimate AA2 displays a smaller standard deviation than AA1 (see Table 2). With regard to the regression coefficients pooled across all sector-years, we can see from Panel B of Table 1 that the average regression slope for the ΔREV – ΔREC term is positive for both regression equations, mirroring the results reported in studies by Jones (1991), Jeter and Shivakumar (1999) and Peasnell et al. (2000). The average slope for current cash flow (OCF) is negative, consistent with Dechow and Dichev's prediction and reported findings (2002: 39, 44) and the empirical evidence reported by Jeter and Shivakumar (1999: 307, Table 2, Panel B).

Table 2 presents the descriptive statistics for all the explanatory variables used in this study's regression models.

The dependent variable for regression equations 4 and 5 is future operating cash flows (OCF_{t+1}): we find positive mean and median results with little evidence of skewness. The positive averages for both current cash flows (OCF) and reported earnings (EARN) are to be expected for a representative sample of UK firms. We can see also that the mean and median values for reported earnings are less than the equivalent values for cash flows – this is consistent with prior UK evidence (Al-Attar and Hussain, 2004).

With regard to our two abnormal accruals metrics (AA1, AA2), averages are close to zero. Although these measures are residuals from OLS regression models, the mean values reported here vary slightly from zero due to the trimming of their extreme percentiles. The Pearson and Spearman correlation coefficients for our abnormal accruals metrics are reported in Table 2, Panel B, but simple bivariate correlation measures are unlikely to give us an appropriate insight into these relationships. Such correlation measures offer no controls for other variables or for the potential impact of bankruptcy risk on the magnitude of the coefficients. However, it may be noted that none of the correlation coefficients for our explanatory variables are close to unity.

3.2. Employing the Subramanyam (1996) disaggregation of total accruals

In this section we present the results for our development of Subramanyam's model, defined in equation 4. Total accruals are disaggregated into normal and abnormal accruals. The regression results for our full sample are reported in Table 3,

Table 1
Abnormal accruals estimation data summarised by sector (across all years 1994–2004)

We estimate abnormal accruals each combination of sector (*s*) and year (*t*) where there are 10 observations or more. All variables are deflated by lagged total assets:

The *PPY model for abnormal accruals* estimation takes the form:

$$WC_{j,s,t} = \alpha_{0,s,t} + \alpha_{1,s,t}.(\Delta REV_{j,s,t} - \Delta REC_{j,s,t}) + \tau_{j,s,t}$$

where $WC_{j,s,t}$ = working capital accruals for firm *j* (in sector *s* and year *t*) = the change in non-cash current assets minus the change in current liabilities; $\Delta REV_{j,s,t}$ = the change in revenues from year *t-1* to *t*; $\Delta REC_{j,s,t}$ = the change in receivables from year *t-1* to *t*; $\alpha_{0,s,t}$ and $\alpha_{1,s,t}$ are the model parameters estimated for sector *s* and year *t*; $\tau_{j,s,t}$ = the residual error (= AA1).

The *cash flow-adjusted PPY model for abnormal accruals* estimation takes the form:

$$WC_{j,s,t} = \theta_{0,s,t} + \theta_{1,s,t}.(\Delta REV_{j,s,t} - \Delta REC_{j,s,t}) + \theta_{2,j,s,t}.OCF_{j,s,t} + \delta_{j,s,t}$$

where $OCF_{j,s,t}$ = cash flows from operations for firm *j* (in sector *s* and year *t*); $\theta_{0,s,t}$, $\theta_{1,s,t}$ and $\theta_{2,s,t}$ are the model parameters estimated for sector *s* and year *t*; $\delta_{j,s,t}$ = the residual error (= AA2).

* indicates rejection of the null hypothesis (zero slope) at the 0.05 level using a two-tailed test and t-ratios for slope estimates across sector-years.
Total number of firm-year observations: 4,024 extracted from *Datastream* for UK firms in the FTSE-100, FTSE Mid-250 and FTSE Small Cap indices.

Table 1
Abnormal accruals estimation data summarised by sector (across all years 1994–2004) *(continued)*

Panel A: Descriptive statistics (across all years 1994–2004)

	WC			*ΔREV – ΔREC*			*OCF*			*Sector-year obs. (n)*		
Sector	Mean	Median	Std Dev	Mean	Median	Std Dev	Mean	Median	Std Dev	Mean	Median	Std Dev
Minerals	0.049	0.018	0.137	0.102	0.052	0.266	0.141	0.118	0.120	13.700	14	1.829
Building & Construction	0.079	0.043	0.156	0.126	0.098	0.266	0.069	0.069	0.088	39.636	39	12.274
Chemicals	0.050	0.013	0.236	0.050	0.031	0.301	0.099	0.097	0.058	17.571	18	4.077
Hotels & Leisure	0.301	0.004	1.852	1.594	0.053	2.602	0.792	0.078	2.523	20.900	21	2.514
Electricals	0.066	0.039	0.221	0.111	0.076	0.380	0.097	0.104	0.126	22.500	23	7.292
Engineering	0.041	0.022	0.144	0.089	0.062	0.294	0.108	0.103	0.075	46.200	46	10.570
Paper & Packaging	0.068	0.034	0.118	0.120	0.091	0.264	0.139	0.118	0.121	14.667	15	1.862
Food	0.018	0.005	0.103	0.084	0.050	0.455	0.108	0.108	0.079	22.900	24	4.228
Household Products	0.029	0.021	0.086	0.132	0.081	0.231	0.143	0.113	0.128	13.000	14	2.449
Healthcare	0.145	0.027	0.513	0.179	0.081	0.370	0.069	0.105	0.272	11.500	12	1.049
Pharmaceuticals	0.061	0.020	0.193	0.137	0.054	0.301	–0.184	–0.129	0.427	14.400	14	4.300
Media	0.097	0.035	0.276	0.178	0.085	0.653	0.112	0.097	0.144	26.900	27	2.470
Retailers	0.059	0.021	0.190	0.216	0.118	0.533	0.125	0.109	0.119	45.545	46	10.671
Pubs, Breweries & Restaurants	0.029	0.004	0.118	0.137	0.055	0.333	0.113	0.098	0.069	15.800	15	2.936
Business Support Services	0.054	0.027	0.175	0.177	0.099	0.502	0.143	0.137	0.155	33.182	36	7.414
IT & Computing	0.202	0.070	1.004	0.311	0.165	0.709	0.100	0.118	0.419	23.818	26	8.010
Transport	0.033	0.012	0.115	0.144	0.049	0.347	0.168	0.102	0.667	21.727	24	5.255
Utilities	0.017	0.006	0.060	0.069	0.024	0.194	0.109	0.094	0.091	20.000	20	3.578

Table 1
Abnormal accruals estimation data summarised by sector (across all years 1994–2004) *(continued)*

Panel B: Regression outputs (across all years 1994–2004)

Sector	*Mean sector-year population*	*Summary (mean) sector regression output for PPY model across years 1994–2004*			*Summary (mean) sector regression output for cash flow-adjusted PPY model across years 1994–2004*			
	n	α_0	α_1	*Adj* R^2	θ_0	θ_1	θ_2	*Adj* R^2
Minerals	13.700	0.043	0.266	0.297	0.013	0.234	0.185	0.318
Building & Construction	39.636	0.009	0.370	0.412	0.107	0.388	–0.453	0.491
Chemicals	17.571	0.109	0.401	0.291	0.010	0.422	–0.186	0.283
Hotels & Leisure	20.900	–0.022	0.187	0.900	–0.022	0.211	–0.045	0.900
Electricals	22.500	–0.033	0.373	0.405	–0.027	0.381	–0.099	0.411
Engineering	46.200	–0.026	0.267	0.338	–0.043	0.249	0.208	0.349
Paper & Packaging	14.667	0.075	0.129	0.096	–0.050	0.043	0.323	0.117
Food	22.900	–0.002	0.149	0.434	–0.009	0.144	0.077	0.432
Household Products	13.000	–0.004	0.124	0.186	–0.030	0.194	–0.217	0.246
Healthcare	11.500	0.247	0.493	0.108	0.273	0.240	–1.386	0.609
Pharmaceuticals	14.400	0.030	0.267	0.176	0.033	0.264	0.012	0.169
Media	26.900	0.030	0.188	0.212	0.034	0.192	–0.068	0.209
Retailers	45.545	–0.018	0.257	0.542	–0.032	0.271	–0.147	0.548
Pubs, Breweries & Restaurants	15.800	–0.011	0.283	0.643	–0.037	0.246	0.279	0.667
Business Support Services	33.182	0.028	0.092	0.075	0.000	0.076	0.264	0.120
IT & Computing	23.818	–0.054	0.465	0.102	0.050	0.609	–2.100	0.832
Transport	21.727	0.200	0.121	0.106	0.021	0.121	–0.005	0.102
Utilities	20.000	0.014	0.198	0.485	0.016	0.204	–0.023	0.475
Regression output pooled across all sector-years	*Mean coeff*:	0.034*	0.257*	0.323	0.017*	0.249*	–0.188*	0.404
	SE (coeff):	0.0067	0.0102	–	0.0063	0.0112	0.0509	–
	t-value:	5.10	25.28	–	2.72	22.30	–3.69	–
	Median:	0.012	0.262	0.294	0.005	0.237	–0.034	0.380

Table 2
Describing the variables employed in the regression analyses

Panel A: Descriptive statistics

- Number of observations = 3,115. This number is smaller than that reported in Table 1 because the regression analysis involves trimming of extreme percentiles and also requires the availability on one-year-ahead data for cash flows.
- All variables deflated by lagged total assets, and trimmed of their extreme percentile observations.

	Mean	*Median*	*Std Dev*	*Minimum*	*Maximum*
OCF_{t+1} †	0.1052	0.1006	0.0952	–0.4008	0.4713
EARN	0.0527	0.0615	0.0898	–0.5600	0.3100
OCF	0.1085	0.1026	0.0971	–0.5015	0.5190
NA1	–0.0523	–0.0439	0.1115	–0.7574	0.6215
NA2	–0.0532	–0.0449	0.1147	–0.7169	0.6377
AA1	–0.0035	–0.0071	0.0846	–0.3988	0.4380
AA2	–0.0025	–0.0057	0.0838	–0.5212	0.4506
AP	0.0160	0.0058	0.0467	–0.1005	0.3438
INV	0.0157	0.0023	0.0489	–0.1194	0.3433
AR	0.0261	0.0098	0.0698	–0.1602	0.5825
DEP	0.0497	0.0439	0.0309	0.0016	0.2082
OTHER	–0.0319	–0.0177	0.0892	–0.6431	0.3260
BR ‡	0.2265	0.0178	0.3516	0	1

where EARN = reported earnings; OCF = Operating cash flows; AP = change in accounts payable; INV = change in inventory; AR = change in accounts receivable; DEP = depreciation on tangible assets; OTHER= represents other accruals {reported earnings – [OCF + AR + INV – AP – DEP]}; AA1 and AA2 = abnormal accruals estimates based on equations 1 and 2 in the main text; NA1 and NA2 = normal accruals defined as total accruals (reported earnings – OCF), less abnormal accruals; BR = bankruptcy risk is measured here using the one-year-ahead LOGIT model developed for UK firms by Charitou et al. (2004).

† This is the main dependent variable for our regression models. The skewness coefficient for this variable is – 0.135

‡ *Upper-bounds for bankruptcy risk probability deciles:*
2.5E-06 (D1); 1.1E-04 (D2); 7.7E-04 (D3); 3.6E-03 (D4); 0.0152 (D5); 0.0501 (D6); 0.1520 (D7); 0.4544 (D8); 0.9220 (D9); 1.000 (D10).

Table 2
Describing the variables employed in the regression analyses *(continued)*

Panel B: Correlation statistics for all explanatory variables used in the regression models

- Number of observations = 3,115.
- Coefficients above (below) the diagonal are Pearson (Spearman) correlations.

	EARN	OCF	NA1	NA2	AA1	AA2	AP	INV	AR	DEP	OTHER	BR
EARN		0.570*	0.278*	0.257*	0.041*	0.060*	0.084*	0.152*	0.168*	0.002	0.215*	–0.604*
OCF	0.592*		–0.335*	–0.376*	–0.100*	–0.032	0.153*	–0.032	0.084*	0.435*	–0.332*	–0.360*
NA1	0.106*	–0.341*		0.940*	–0.639*	–0.599*	–0.339*	–0.192*	–0.332*	–0.370*	0.704*	–0.181*
NA2	0.089*	–0.380*	0.943*		–0.533*	–0.657*	–0.335*	–0.157*	–0.312*	–0.386*	0.689*	–0.162*
AA1	0.048*	–0.096*	–0.588*	–0.500*		0.891*	0.360*	0.451*	0.520*	–0.009	–0.319*	0.011
AA2	0.080*	–0.023	–0.574*	–0.610*	0.896*		0.370*	0.413*	0.510*	0.026	–0.328*	–0.009
AP	0.127*	0.207*	–0.325*	–0.315*	0.328*	0.325*		0.474*	0.610*	0.099*	–0.262*	0.035
INV	0.228*	0.053*	–0.138*	–0.126*	0.383*	0.368*	0.482*		0.307*	–0.034	–0.365*	–0.099*
AR	0.209*	0.114*	–0.301*	–0.280*	0.497*	0.482*	0.567*	0.403*		0.101*	–0.519*	–0.001
DEP	0.117*	0.489*	–0.401*	–0.413*	–0.014	0.030	0.104*	0.010	0.113*		–0.134*	0.024
OTHER	0.005	–0.305*	0.616*	0.607*	–0.267*	–0.290*	–0.264*	–0.333*	–0.462*	–0.128*		–0.135*
BR	–0.646*	–0.409*	–0.134*	–0.119*	–0.013	–0.017	0.026	–0.107*	0.016	–0.012	–0.088	

* indicates significance at the 0.05 level using a two-tailed test.

Table 3
Explaining future cash flows via current cash flows and accruals

Panel A: Regression results for the full sample

$$OCF_{it+1} = \lambda_0 + \lambda_1 OCF_{i,t} + \lambda_2 AA_{i,t} + \lambda_3 NA_{i,t} + \lambda_4 BR_{i,t} + \lambda_5 BR{\cdot}OCF_{i,t} + \lambda_6 BR{\cdot}AA_{i,t} + \lambda_7 BR{\cdot}NA_{i,t} + w_{i,t+1}$$

where OCF = operating cash flows; AA = abnormal accruals (for which we use two measures, AA1 and AA2 defined by equations 1 and 2); NA = normal accruals, defined as total accruals less abnormal accruals; BR = one-year-ahead bankruptcy risk, following Charitou et al. (2004); λ_0 to λ_n= model parameters, to be estimated using OLS regression; $w_{i,t+1}$ = random error term following usual OLS assumptions. All variables deflated by lagged total assets.

H_0: slope = 0 for all variables.
H_1: slope > 0 for the variables OCF, NA, AA.
H_1: slope < 0 for the variable BR, BR·OCF, BR·NA, BR·AA.
H_1: slope ≠ 0 for the constant (intercept).

* indicates significance (rejection of null hypothesis H_0) at the 0.05 level

Dep. Variable: OCF_{t+1}
Adj R-sq. 0.455
Model F stat (zero slopes): 371.84*
Observations: 3,115

	Coeff.	*SE*	*t-ratio*
Intercept	0.0326	0.0030	10.93*
OCF	0.8381	0.0290	28.90*
AA1	0.3423	0.0375	9.13*
NA1	0.3836	0.0342	11.20*
BR	–0.0036	0.0055	–0.65
BR·OCF	–0.1153	0.0395	–2.92*
BR·AA1	–0.2638	0.0560	–4.71*
BR·NA1	–0.2813	0.0431	–6.52*

Dep. Variable: OCF_{t+1}
Adj R-sq. 0.456
Model F stat (zero slopes): 372.65*
Observations: 3,115

	Coeff.	*SE*	*t-ratio*
Intercept	0.0325	0.0030	10.93*
OCF	0.8374	0.0290	28.88*
AA2	0.3413	0.0379	9.01*
NA2	0.3766	0.0342	11.02*
BR	–0.0037	0.0054	–0.68
BR·OCF	–0.1138	0.0395	–2.89*
BR·AA2	–0.2645	0.0571	–4.63*
BR·NA2	–0.2749	0.0430	–6.39*

Table 3
Explaining future cash flows via current cash flows and accruals *(continued)*

Panel B: Regression results for the upper decile by bankruptcy risk

$$OCF_{i,t+1} = \lambda_0 + \lambda_1 OCF_{i,t} + \lambda_2 AA_{i,t} + \lambda_3 NA_{i,t} + w_{i,t+1}$$

where OCF = operating cash flows; AA = abnormal accruals (for which we use two measures, AA1 and AA2 defined by equations 1 and 2); NA = normal accruals, defined as total accruals less abnormal accruals; λ_0 to λ_n= model parameters, to be estimated using OLS regression; $w_{i,t+1}$ = random error term following usual OLS assumptions. All variables deflated by lagged total assets.

H_0: slope = 0 for all variables.
H_1: slope > 0 for the variables OCF, NA, AA.
H_1: slope ≠ 0 for the constant (intercept).

* indicates significance (rejection of null hypothesis H_0) at the 0.05 level

Dep. Variable: OCF_{t+1}
Adj R-sq. 0.524
Model F stat (zero slopes): 114.33*
Observations: 310

	Coeff.	*SE*	*t-ratio*
Intercept	0.0276	0.0070	3.93*
OCF	0.7592	0.0419	18.11*
AA1	0.0418	0.0645	0.65
NA1	0.0937	0.0392	2.39*

Dep. Variable: OCF_{t+1}
Adj R-sq. 0.524
Model F stat (zero slopes): 113.86*
Observations: 310

	Coeff.	*SE*	*t-ratio*
Intercept	0.0273	0.0070	3.87*
OCF	0.7608	0.0421	18.08*
AA2	0.0422	0.0668	0.63
NA2	0.0924	0.0391	2.36*

Panel A, with separate regressions for our two measures of abnormal accruals (AA1, AA2). The interactive variables allow us to examine whether the relationships between future cash flows and current earnings components (cash flows, normal accruals and abnormal accruals) vary with the level of one-year-ahead bankruptcy risk.

In Table 3, Panel A, it can be seen that the slope coefficients for our two measures of abnormal accruals (AA1, AA2) are positive and significant at the 0.05 level. The slopes for both current cash flows and normal accruals are also positive, consistent with Subramanyam's findings for US firms. These results provide evidence of the explanatory power of current cash flows, normal and abnormal accruals vis-à-vis future cash flows, and a rationale for the pricing of these data in the marketplace. However, the bankruptcy-interaction variables all generate negative and significant slopes. This point relates to how bankruptcy risk (BR) impacts the relationship between current accounting data and future cash flows. The significant negative slopes for the multiplicative variables in equation 4 indicate that the strong positive associations observed for OCF, NA and AA become notably reduced at higher levels of bankruptcy risk.

We investigate this issue further by re-estimating regression equation 4 for individual bankruptcy risk deciles.[7] Our investigations reveal that there is a breakdown in the association between abnormal accruals and future cash flows for the upper decile of risky firms: these results are presented in Table 3, Panel B. While the regression slopes for our abnormal accruals estimates (AA1, AA2) remain positive, they are no longer significant even at the 0.10 level.

We find that although coefficients for OCF, NA and AA retain their positive signs, they are all smaller for firms in this decile than for the main sample (see Table 3, Panel A). This makes sense given that the relationship between the three independent variables and future cash flows depends not only on their own respective slope coefficients (all positive in Panel A), but also on the coefficient for each respective interactive variable (all negative in Panel A). For example, a unit change in AA1 is expected to be associated with a change in future cash flows equal to $\{0.3423 - (0.2638 \cdot \mathrm{BR})\}$. In this decile, bankruptcy probabilities range from 0.92 to unity. If the BR variable is close to unity, the impact of the negative coefficient will be notable and the overall impact is to reduce the relationship to an insignificant level. Several recent studies suggest that firms in severe financial distress often exhibit volatile and extreme abnormal accruals (Rosner, 2003; Butler et al., 2004); these matters are discussed further in section 3.3.

A number of untabulated results are worth noting here. Regression results for the ninth risk decile – where the probability of failure is between 0.46 and 0.92 – generate results consistent with the main body of firms (i.e. positive coefficients for current cash flows, normal and abnormal accruals). However, again the slopes for the explanatory variables are smaller than for the overall sample. For example, the coefficients for AA1 and AA2 are 0.198 and 0.205 respectively. These findings support our original decision to include the interactive variables in our model. Thus, the explanatory power of current accounting data (OCF, NA, AA) for future cash flows appears to be a declining function of bankruptcy risk.

We also examine the equivalent coefficient estimates for the lowest bankruptcy risk deciles: the slope coefficients of the three variables (OCF, NA, AA) for the lowest risk decile are all positive and significant at the 0.05 level. The null hypothesis of a zero slope is rejected at the 0.026 and 0.008 levels for AA1 and AA2, respectively. Thus, there is no evidence for the non-linear impact of bankruptcy risk reported in Hanna's price-based US study, where both the upper and lower bankruptcy risk quintiles demonstrated insignificant associations between current data and future cash flows, as proxied by stock returns.

A final point relates to sample size. A casual inspection of Table 1 shows that when estimating abnormal accruals, the numbers of observations used varies across different sector-years. A number of sector-years average 30 or more observations while other sector-years average little more than our minimum requirement of 10 observations. To assess our study's sensitivity to these differences, we conduct our main analysis on two sub-samples: one containing observations from the four most populated sectors and a second containing the remaining smaller sectors. We find that our original findings hold for both sub-samples.

3.3. Employing the Barth et al. (2001) disaggregation of total accruals

Barth et al. (2001) report that the disaggregation of total accruals into individual accruals items provides an improved insight into future cash flows: Subramanyam does not examine this dimension. We begin by estimating regression equation 5. The regression results presented in Panel A of Table 4 confirm earlier results for US data (Barth et al., 2001) and UK data (Al-Attar and Hussain, 2004), generating positive slopes for current year operating cash flows, depreciation, changes in accounts receivable and inventory, and a negative slope for changes in accounts payable. We also include dummy variables for years and sectors, though

[7] The splitting of the sample by bankruptcy risk means that BR is implicitly controlled for each sample so the interactive variables are removed from the regressions.

these are primarily to control for year effects and industry sector effects in the level of cash flows.

It is the residuals from the Barth et al. model that will be employed here. If a large portion of future cash flows can be explained when accruals items are broken down into individual components then it is possible that the explanatory power released through this disaggregation of accruals may exhaust the information content of abnormal accruals identified in Subramanyam's study. By examining the residuals of equation 5, denoted RESID here, we can investigate whether the disaggregation of total accruals into normal and abnormal accruals reveals additional explanatory power. We would not expect total accruals to possess any significant explanatory power for RESID since equation 5 contains all accrual elements as explanatory variables. However, our aim is to look at the normal and abnormal elements of total accruals and to allow their coefficients to vary with bankruptcy risk as in equation 4. This is done through estimation of equation 6.

The results for this model are reported in Table 4, Panel B, with separate regressions for our two measures of abnormal accruals (AA1 and AA2). We find that the regression coefficients take the same signs for RESID as for future cash flows (reported in Table 3, Panel A) indicating that abnormal accruals contain explanatory power for the residual portion of future cash flows from the Barth et al. model. Normal accruals also exhibit a significant association with the residual. Of course, while the Barth et al. model controls for the explanatory power of individual accruals items it does not distinguish between normal and abnormal accruals, nor does it allow the impact of the accrual components to vary with bankruptcy risk. The low R-squared values are to be expected given that we are examining residuals where the variation explained by current cash flows and individual accruals items has already been stripped-out.

Overall, our results are supportive of Subramanyam's finding that both normal and abnormal accruals map to future cash flows, but this mapping is conditional on bankruptcy risk. Given the negative coefficients for the multiplicative variables, this positive mapping of accruals is most likely in cases of low bankruptcy risk. Thus, for healthy firms it appears that abnormal accruals are not primarily the results of noisy management estimates but instead convey useful information to the market. However, this association appears to weaken for the sub-set of high bankruptcy risk firms.

A possible explanation for this reduced information content is the greater heterogeneity of abnormal accruals in cases where firms are experiencing financial distress. Butler et al. (2004: 141, 156)

Table 4
Earnings components and residual future cash flows

Panel A: Regression of future cash flows onto current earnings components

$$OCF_{i,t+1} = \gamma_0 + \gamma_1 OCF_{i,t} + \gamma_2 AP_{i,t} + \gamma_3 INV_{i,t} + \gamma_4 AR_{i,t} + \gamma_5 DEP_{i,t} + \gamma_6 OTHER_{i,t} + \sum_{m=1}^{9} \gamma_{6+m}.YEAR_m + \sum_{g=1}^{17} \gamma_{15+g}.SECTOR_g + u_{i,t+1}$$

where OCF = Operating cash flows; AP = change in accounts payable; INV = change in inventory; AR = change in accounts receivable; DEP = depreciation on tangible assets; OTHER= represents other accruals {reported earnings – [OCF + AR + INV – AP – DEP]}; γ_0 to γ_n = model parameters, to be estimated using OLS regression. The error term ($u_{i,t+1}$) is the residual (RESID) employed in equation 6 and in Panel B of this table. All variables deflated by lagged total assets.

Sector dummies: Minerals (100); Building & Construction (210); Chemicals (232); Hotels & Leisure (242); Electricals (252); Engineering (261); Paper & Packaging (282); Food (333); Household Products (342); Healthcare (360); Pharmaceuticals (370); Media (432); Retailers (452); Pubs, Breweries & Restaurants (470); Business Support Services (481); Information Technology & Computing (487); Transport (490); Utilities (600).

Year dummies: YEAR1994 to YEAR2003.

Our model includes *m* year dummies for 1994 to 2003, with 2001 being the omitted year dummy; and g sector dummies, with utilities being the omitted sector dummy.

H_0: slope = 0 for all variables.
H_1: slope > 0 for the variables AR, INV, DEP and OCF.
H_1: slope < 0 for the variable AP.
H_1: slope ≠ 0 for the constant (intercept), OTHER, and all year and sector dummies.

* indicates significance (rejection of null hypothesis H_0) at the 0.05 level

Table 4
Earnings components and residual future cash flows *(continued)*

Panel A: Regression of future cash flows onto current earnings components *(continued)*

Dep. Variable: OCF_{t+1}

Adj R-sq. 0.489
Model F stat (zero slopes): 94.25*
Observations: 3,115

		Coeff.	*SE*	*t-ratio*
Earnings components	Intercept	0.0198	0.0070	2.83*
	OCF	0.6727	0.0163	41.28*
	AP	–0.4605	0.0379	–12.15*
	INV	0.1919	0.0322	5.96*
	AR	0.3193	0.0267	11.98*
	DEP	0.2662	0.0472	5.65*
	OTHER	0.2672	0.0187	14.28*
Sector dummies	Sector 100	0.0187	0.0088	2.14*
	Sector 210	–0.0079	0.0067	–1.18
	Sector 232	–0.0034	0.0086	–0.39
	Sector 242	0.0008	0.0076	0.10
	Sector 252	–0.0036	0.0076	–0.48
	Sector 261	0.0032	0.0064	0.50
	Sector 282	0.0074	0.0098	0.75
	Sector 333	0.0031	0.0073	0.42
	Sector 342	0.0083	0.0094	0.88
	Sector 360	0.0024	0.0107	0.22
	Sector 370	–0.0520	0.0096	–5.45*
	Sector 432	0.0061	0.0073	0.83
	Sector 452	0.0042	0.0064	0.66
	Sector 470	0.0092	0.0079	1.16
	Sector 481	0.0032	0.0068	0.46
	Sector 487	–0.0125	0.0083	–1.51
	Sector 490	0.0063	0.0074	0.85
Year dummies	Year 1994	0.0020	0.0063	0.31
	Year 1995	0.0112	0.0053	2.10*
	Year 1996	0.0168	0.0053	3.18*
	Year 1997	0.0004	0.0054	0.08
	Year 1998	–0.0009	0.0055	–0.16
	Year 1999	–0.0086	0.0056	–1.55
	Year 2000	–0.0065	0.0057	–1.13
	Year 2002	0.0051	0.0057	0.90
	Year 2003	0.0109	0.0074	1.48

Table 4
Earnings components and residual future cash flows *(continued)*

Panel B: Residual error, current cash flows and accruals

where RESID = the residuals from regression equation 5 (see Panel A); AA = abnormal accruals (for which we use two measures, AA1 and AA2 defined by equations 1 and 2); NA = normal accruals, defined as total accruals less abnormal accruals; BR = one-year-ahead bankruptcy risk, following Charitou et al. (2004); μ_0 to μ_5 = model parameters, to be estimated using OLS regression; $\zeta_{i,t+1}$ = random error term following usual OLS assumptions.

H_0: slope = 0 for all variables.
H_1: slope > 0 for the variables NA, AA.
H_1: slope < 0 for the variable BR, BR·NA, BR·AA.
H_1: slope ≠ 0 for the constant (intercept).

* indicates significance (rejection of null hypothesis H_0) at the 0.05 level

Dep. Variable: RESID
Adj R-sq. 0.0108
Model F stat (zero slopes): 6.80*
Observations: 3,115

	Coeff.	*SE*	*t-ratio*
Intercept	0.0041	0.0017	2.39*
BR	–0.0142	0.0044	–3.21*
AA1	0.0534	0.0244	2.19*
NA1	0.0785	0.0197	3.99*
BR·AA1	–0.1633	0.0466	–3.51*
BR·NA1	–0.1805	0.0319	–5.66*

Dep. Variable: RESID
Adj R-sq. 0.0102
Model F stat (zero slopes): 6.38*
Observations: 3,115

	Coeff.	*SE*	*t-ratio*
Intercept	0.0040	0.0017	2.37*
BR	–0.0142	0.0044	–3.22*
AA2	0.0602	0.0253	2.38*
NA2	0.0732	0.0195	3.76*
BR·AA2	–0.1733	0.0483	–3.59*
BR·NA2	–0.1754	0.0317	–5.54*

report that failing firms may reduce non-cash net working capital due to liquidity constraints and engage in liquidity enhancing transactions that result in large negative accruals. Indeed, Butler et al. find that bankruptcy risk is not only associated with the sign of abnormal accruals but with the magnitude, with the largest (absolute) values being associated with failing firms. Rosner (2003: 394) hypothesises that the nature of abnormal accruals for failing firms may vary with audit opinions and reports that going-concern opinions are associated with income-decreasing accrual behaviour but income-increasing accruals occur for similar firms where no going-concern opinion is issued. Thus, among failing firms it is likely that accruals data will be more heterogeneous in nature than for healthy firms (Rosner) and that there will be a subset of failing firms with very large negative abnormal accruals (Butler et al.).

We find that, in general, there is a positive association between abnormal accruals for UK firms and one-year-ahead operating cash flows. Our findings could also be considered supportive of Subramanyam's suggestion that managers may sometimes use accruals to signal future profitability. If this is true, in the case of firms with negative abnormal accruals these results may not reflect a desire to signal future bad news but may reflect the phenomenon noted by Butler et al. (2004: 141) in which some distressed companies generate extreme negative accruals through their liquidity-enhancing activities.

4. Conclusion

This study examines the association between earnings components and future cash flows, building on Subramanyam (1996). Earnings data are decomposed into cash flows, normal accruals and abnormal (discretionary) accruals, and are then used to explain one-year-ahead cash flows within an OLS regression framework. Given that unusually large accruals are often linked to excessive estimation errors and reduced earnings quality (Dechow and Dichev, 2002; Richardson, 2003) or deliberate earnings management, it is not obvious that the market should price abnormal accruals and yet evidence for this exists (Subramanyam, 1996; Xie, 2001). A possible explanation is that abnormal accruals convey useful information regarding future cash flows. This was the conclusion of Subramanyam's US study and we have found similar results for UK firms. However, we also take account of bankruptcy risk, which has been reported to reduce the usefulness of accounting data for assessing future cash flows in several price-based studies (Frankel, 1992; Hanna, 1995).

We conclude that Subramanyam's findings hold true for the main body of UK firms suggesting that, on average, abnormal accruals are not simply the product of noisy accruals-estimation by managers but contain useful information for market participants. The explanatory power of abnormal accruals for future cash flows declines at higher levels of bankruptcy risk and becomes insignificant for the upper decile of risky firms. Thus, with the exception of very high-risk firms, we find that there is a rationale for the market's pricing of abnormal accruals. We also examine whether the disaggregation of total accruals into individual accruals items (see Barth et al., 2001; Al-Attar and Hussain, 2004) exhausts the information content of abnormal accruals. We find this not to be the case – abnormal accruals retain a small but significant degree of explanatory power, reiterating our previous findings.

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